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# IMPACT ANALYSIS FROM DRIVING PATTERNS AND ENVIRONMENTAL CONDITIONS ON THE OPERATIONAL RANGE OF ELECTRIC VEHICLES

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**ABSTRACT**

As the power sector decarbonizes, transport becomes the main driver of CO2 emissions growth. However, sustainable road transportation is nowadays achievable throughout the electrification of propulsion systems as it represents a promissory to achieve the climate goals. In this paper, a library developed using the object-oriented mathematical modelling language Modelica was used to simulate the impact of different driving behaviors, more specifically top-speed and acceleration rate, on the operational range of an electric vehicle. Results found differences over 50% on the operational range of the vehicle with different acceleration rates and cruise speeds selected. Furthermore, this paper analyzed the impact of external environmental conditions on the battery range. It was found that sub-zero temperatures could reduce driving range by over 17%. These results offer great insights for successful implementations of eco-driving modes on electric vehicles, as well as designing efficient driving strategies for autonomous cars.

**Keywords:** Electric Vehicles, Mathematical Modelling, Modelica, Range Anxiety, Driving behavior

## 1. INTRODUCTION

Sustainable road transportation is nowadays achievable throughout the electrification of propulsion systems as it represents a promissory way to fulfill the traced goals by the United Nations in the Paris Agreement. Battery-electric vehicles (BEV) offer multiple advantages over their conventional counterparts, for instance, when charged using renewable energy, their greenhouse gases (GHG) footprint reduces significantly. Furthermore, regenerative braking, state-of-the-art motors and power conversion technologies increase their operation efficiency, and finally, consumer reports have reported an overall better experience [1]. In consequence, several strategies, including short and long term policies have been implemented to increase the market uptake of BEVs [2].

This has led to an increase in BEV sales: approximately 750 thousand vehicles new vehicles were sold in 2016, which accounts for 2 million vehicles on the roads, almost twice the amount of 2015 [3].

BEVs, however, face several challenges. First of all, their price is higher compared with hybrid electric vehicles (HEV) and ICE cars. Secondly, the battery pack accounts for a great share of the overall cost [4][5]. Furthermore, their operational range operation might cause users experience the fear that the vehicle will not reach its destination or charging station because of the battery will run out of power, a common phenomenon found on first-time EV owners, known as range anxiety [6].

Although the market uptake of BEVs is growing up, highly detailed operational profiles datasets for EVs are often proprietary and the majority of public information available is obtained from limited demonstration projects and statistically-build datasets, fixed to specific operation conditions [7]. Therefore, to analyze the impact of the overall range for different driving patterns, mathematical models, able to calculate the kinematics of the vehicle, are required [8].

Several authors have addressed the issue of energy efficiency in electric vehicles, however, the authors could not find specific analysis for energy consumption depending only on acceleration and top-speed parameters, for instance: Grunditz and Thiringer focus on motor losses and the consequences of varying motor parameters on the acceleration time [10]; Ahmadi et al [11], use several energy management strategies for improving fuel economy and performance of FC-hybrid vehicles and Martinez et al [12], studied the performance of an electric vehicle over a quarter mile to determine the best storage technology required.

The purpose of this study is to assess the BEVs' operational range under several driving patterns and environmental conditions. A previously developed library for modeling EVs, presented in [13] was used, where a Chevrolet Bolt was modelled. This paper is structured as follows: The next section describes the electric vehicle modelling strategy and the design of different driving patterns. Section 3 presents and analyzes the results obtained from using the defined driving patterns on the BEV model. Finally, Section 4 summarizes the main results of this work.

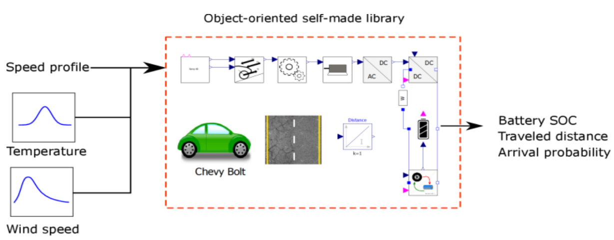


Fig. 1. A visual representation of the developed library

## 2. METHODOLOGY

The driving patterns were coded in MatLab (2015b, MathWorks) in three groups: constant cruise speed, constant acceleration and a combination of both. First, multiple simulations were carried out using these driving profiles and the operational EVs range was obtained from the simulation model. Secondly, in order to analyze the impact of different environmental conditions, a Monte Carlo simulation was carried out changing the external variables of temperature and wind speed. All the simulations were performed using OpenModelica 1.13.

### *2.1 Electric vehicle modelling*

A library to estimate the operational range of two commercial EVs, using the Modelica Language was used. Detailed information about the mathematical modelling, vehicle's parameters and model limitations are presented in [13]. Models were validated using the New European Driving Cycle (NEDC) and the range was compared with manufacturer's data. In this particular study, all the tests were carried out on the Chevy Bolt model. A visual representation of the model, inputs and outputs are presented in Fig. *1*.

### *2.2 Driving patterns definition*

People's driving patterns varies with several factors, for instance: traffic conditions, road quality, anxiety, among others. Therefore, the task of modeling a standard driving pattern is not straightforward. Driving behaviors can be defined from the acceleration and braking periods [14]. Thus, aggressive patterns could be modeled from abrupt acceleration and braking events.

#### *2.2.1 Constant velocity profiles*

Aerodynamic losses in any vehicle increases with the cube of the velocity and in consequence, accounts for a large share of the required force to power the vehicle when driving [15]. Then, several scenarios were defined for different cruise speeds from the lowest to the top speed, 147 Km per hour.

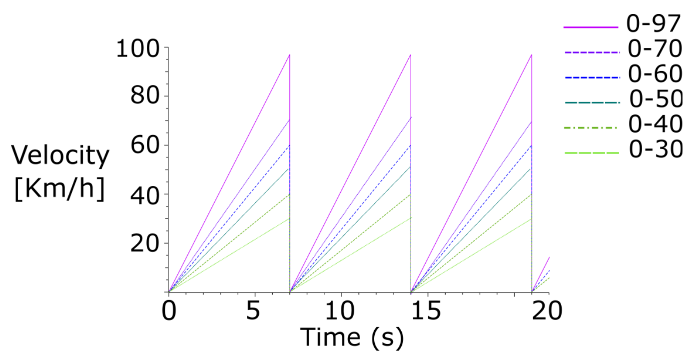


Fig. 2. Constant acceleration driving profiles

#### *2.2.2 Constant acceleration profiles*

Abrupt acceleration and braking events require the battery pack and power converter to deliver an amount of current that depends directly on the acceleration [16]. Furthermore, in Lithium-based battery technology, current outputs above the rated 1-C current, lead to sharp changes on its internal resistance value, thus reducing its operational energy capacity [17]. To test this out, three constant acceleration profiles were designed and are presented in Fig. *2*. These patterns were repeated until the battery pack reached 20% charge level (SOC).

#### *2.2.3 Quarter mile*

The energy performance was measured in kWh/km using a standard quarter mile setup, often used in drag-racing, where the vehicle was simulated using different constant-acceleration slope as presented in Fig. 3. For each one, the impact on energy performance was recorded.

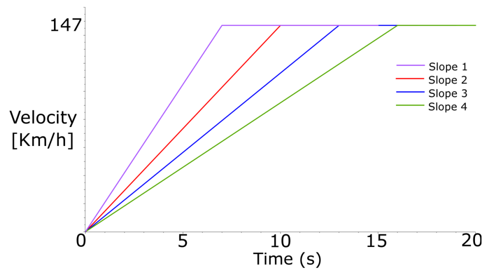


Fig. 3. Driving slopes for quart mile tests

### *2.3 Environmental Conditions testing using Monte Carlo Simulations*

A simulation scenario was designed to test the arrival probability of the modelled BEV in a quarter mile using a constant acceleration ramp. Since the model assumed a discharged battery when the charge level falls below 20%, we established an initial SOC of 21% to reduce simulation time. A linear relationship between the battery's capacity and temperature was considered, as proposed by [18]. To model the environmental variables of temperature and wind speed a Monte Carlo method was used. Fifty (50) Monte Carlo simulations were carried out for the selected BEV model, in two extreme scenarios at different temperatures and wind speeds. The parameters of the probability distributions used are presented in Table 1.

Table 1. Uncertainty Models Used

| **Environmental Input** | **Probability Distribution** | **Parameters** |
|---|---|---|
| Wind Speed | Weibull | $\lambda = 6, \ k = 10$ |
| Temperature | Normal | *Hot* $(\mu = 30, \ \sigma = 5)$<br>*Cold* $(\mu = -20, \ \sigma = 5)$ |

## 3. RESULTS

On this section, results from the scenarios defined in Section 3 for the used model are presented. The impact on the operational range of the simulated BEV for the driving profiles for different cruise speeds and constant acceleration rates are summarized on Fig. 4. The main reason why the operational range decreases at lower speeds is due to the fact that the electric motor efficiency decreases at low speeds [19]. It was found that the range is the highest when the driver holds a cruise speed of approximately 50 km/h.

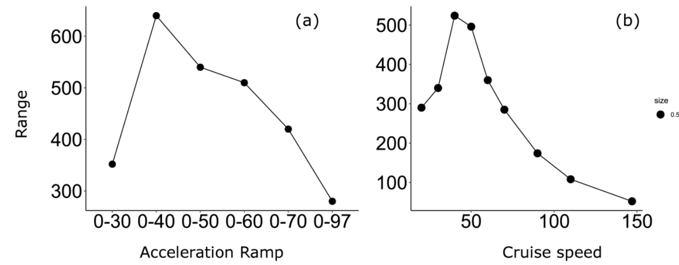


Fig. 4. Driving range for acceleration ramps and cruise speeds

Analyzing the acceleration factor, results provided by the tests conducted in a quarter mile demonstrated that there is a considerable increase in the energy consumption between slope 1 and the rest. The energy consumption per 400 m were, from Slope 1 to Slope 4, respectively: 0.4018, 0.3321, 0.2696, and 0.2026 respectively for each slope.

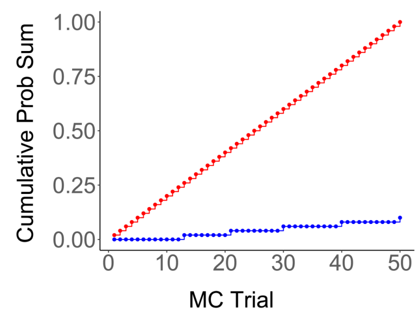


Fig. 5. Cumulative arrival probability on each MC trial

Finally, the impact of the wind speed and outdoor temperature on the operational range of the BEV is presented in Fig. 5. This plot shows the cumulative sum of the arrival probability to the desired destination on each MC trial. This experiment shows that during extreme warm conditions the probability of arrival was not shaped. On the contrary, the arrival probability was shaped by extreme cold temperatures, since only on a 10% of the total number of simulations, the EV successfully arrived. Additionally, range reductions in of up to 17% at -20 °C and 9.4 m/s were obtained.

## 4. CONCLUSIONS

This work has presented the capabilities of an object-oriented open-source model developed using the modelling language Modelica, for evaluating the impact of different driving patterns and environmental variables on the operational range of EVs as well as introducing uncertainty in mathematical models by using Monte Carlo simulations. Results suggested that substantial energy savings can be achieved on BEVs by shaping the way the driver accelerates as well as the cruise speed used. Additionally, regarding environmental conditions, extreme low-temperature values considerably reduce the available range while wind speed and high temperatures values do not affect it as much. These results offer great insights for successful implementations of eco-driving modes on electric vehicles, as well as designing efficient driving strategies for autonomous cars.

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